*DNN*s as Applied to Electromagnetics, Antennas, and Propagation - A Review

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***Abstract*—A review of the most recent advances in deep learning (*DL*) as applied to electromagnetics (*EM*), antennas, and propagation is provided. It is aimed at giving the interested readers and praticitioners in *EM* and related applicative fields some useful insights on the effectiveness and the potentialities of deep neural networks (*DNN*s) as computational tools with an unprecedented computational efficiency. The range of considered applications includes forward/inverse scattering, direction-of-arrival (*DoA*) estimation, radar and remote sensing (*RS*), and multi-input/multi-output (*MIMO*) systems. Appealing *DNN*-based solutions concerned with localization, human behavior monitoring (*HBM*), and *EM* compatibility (*EMC*) are reported, as well. Some final remarks are drawn along with indications on future trends according to the authors' viewpoint.**

***Index Terms*—Deep Learning, Deep Neural Networks, Convolutional Neural Networks, Electromagnetics, Antennas, Propagation, Scattering, Radar, Remote Sensing.**

I. Introduction

DEEP learning (*DL*) is rapidly emerging as a powerful framework enabling unprecedented time and accuracy performance for solving complex problems in electromagnetics (*EM*) [1]-[8]. As a matter of fact, the number of *DL*-related publications has been exponentially growing during the last five years as confirmed by the *IEEE-Xplore* database [Fig. 1(*a*)]. Indeed, *DL*, machine learning (*ML*), and artificial intelligence (*AI*) are currently listed in the *top ten* most popular search keywords. Although the development of *EM* techniques based on deep neural networks (*DNN*s) is at the beginning, many researches have been recently carried out in forward/inverse *EM* scattering [1][2], direction-of-arrival (*DoA*) estimation [3], radar and remote sensing (*RS*) [4], and multiple-input/multiple-output (*MIMO*) systems [5]. Moreover, an ever-growing number of papers has been published on localization [6], human behavior monitoring (*HBM*) [7], and *EM* compatibility (*EMC*) [8], as well.

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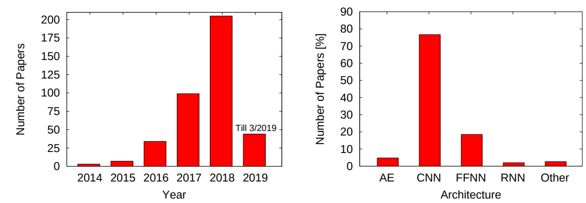

(*a*) (*b*)

Figure 1. *DNN Techniques in EM* - Statistics of (*a*) number of papers vs. year and (*b*) percentage distribution vs. *ML* architecture (based on *IEEE-Xplore* database updated to March 2019).

The purpose of this letter is that of reviewing the most recent advances of *DNN*s as applied to *EM* at large. Towards this end, Section II briefly summarizes the most common *DNN* architectures, while Sect. III provides an overview of their *EM* applications. Finally, some final remarks are drawn, while potential future trends are envisaged (Sect. IV).

II. *DNN* Architecture

Analogously to learning-by-examples (*LBE*) techniques such as support vector machines (*SVM*s) and Gaussian Processes (*GP*s) [9], *DNN*s are *ML* algorithms aimed at learning a non-linear (*NL*) function, $\underline{\Phi}$, starting from a database of T *I/O training* pairs $\mathcal{D} = \{[\underline{\Omega}_t, \underline{\Phi}(\underline{\Omega}_t)]; t = 1, ..., T\}$, $\underline{\Omega}_t$ being the t-th ($t = 1, ..., T$) K-dimensional input sample ($\underline{\Omega}_t = \{\Omega_{k,t}; k = 1, ..., K\}$), while $\underline{\Phi}(\underline{\Omega}_t)$ is the corresponding Q-dimensional output ($\underline{\Phi}(\underline{\Omega}_t) = \{\Phi_q(\underline{\Omega}_t); q = 1, ..., Q\}$) for *regression* problems or one ($Q = 1$) integer label (i.e., $\underline{\Phi} \equiv \Phi_1(\underline{\Omega}_t) \in \mathbb{Z}$) in case of *classification* [9]. *DNN*s are composed by a significantly higher number of layers, L, and neurons (processing units) than *shallow NN*s [9] [1] to accurately approximate ($\underline{\widetilde{\Phi}} \approx \underline{\Phi}$) much less predictable *I/O* relationships during the *on-line* phase [10]-[12]. Although many deep architectures exist, including auto-encoders (*AE*s), feed-forward *NN*s (*FFNN*s), and recurrent *NN*s (*RNN*s) [12], more than 75% of surveyed works rely on convolutional *NN*s (*CNN*s or *ConvNets*) [Fig. 1(*b*)]. Without loss of generality, in the simplest case (Fig. 2) the *CNN* prediction $\underline{\widetilde{\Phi}}(\underline{\Omega})$ for an input sample $\underline{\Omega}$ can be described as that of a single-layer fully connected *NN* (*FCNN*) [9]

$$\widetilde{\Phi}_q(\underline{\Omega}) = \psi\left\{\sum_{m=1}^{M}\sum_{n=1}^{N} w_{mn}^{q}\mathcal{O}_{mn}^{(L)}\right\}; \quad q = 1, ..., Q \qquad (1)$$

where $\{w_{mn}^q; m = 1, ..., M; n = 1, ..., N\}$ are the *FCNN* weights for the q-th output ($q = 1, ..., Q$) [11] and $\psi\{\,.\,\}$

[1]Commonly, the threshold at which *shallow learning* ends and *DL* begins is $L \geq 10$ [10].

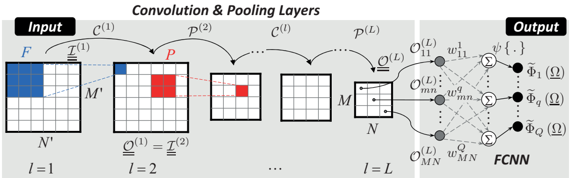

Figure 2. *Deep CNNs* - Block scheme of a typical *CNN* network.

is a *NL activation* function such as the rectified linear unit (*ReLU*) function, $\psi\{\chi\} = \max(0, \chi)$. Moreover, $\mathcal{O}_{mn}^{(L)}$ is the (m, n)-th ($m = 1, ..., M$; $n = 1, ..., N$) entry of the $(M \times N)$ matrix $\underline{\underline{\mathcal{O}}}^{(L)}$, which is the $2D$ output (*feature map*) of the last ($l = L$) *CNN* layer. The feature map is the result of a nested sequence of *convolution*, $\mathcal{C}^{(l)}\{\,.\,\}$, and *pooling*, $\mathcal{P}^{(l)}\{\,.\,\}$, operations carried out by the corresponding *CNN* layers on the input to the first ($l = 1$) one, $\underline{\underline{\mathcal{I}}}^{(1)}$, of dimension $(M' \times N') > (M \times N)$ whose (m', n')-th entry is given by $\mathcal{I}_{m'n'}^{(1)} = \Omega_{n'+(m'-1)\times N'}$:

$$\underline{\underline{\mathcal{O}}}^{(L)} = \mathcal{P}^{(L)}\left\{\mathcal{C}^{(L-1)}\left[\mathcal{P}^{(L-2)}\left(...\mathcal{C}^{(1)}\left\{\underline{\underline{\mathcal{I}}}^{(1)}\right\}...\right)\right]\right\}. \quad (2)$$

With reference to the input and the output of the l-th ($l = 1, ..., L$) layer, $\underline{\underline{\mathcal{I}}}^{(l)}$ and $\underline{\underline{\mathcal{O}}}^{(l)}$ ($\underline{\underline{\mathcal{O}}}^{(l)} = \underline{\underline{\mathcal{I}}}^{(l+1)}$), the result of the l-th *convolution* layer, $\underline{\underline{\mathcal{O}}}^{(l)} \triangleq \mathcal{C}^{(l)}\left\{\underline{\underline{\mathcal{I}}}^{(l)}\right\}$, is equal to

$$\mathcal{O}_{mn}^{(l)} = \psi\left\{\sum_{u=1}^{F}\sum_{v=1}^{F}\mathcal{K}_{uv}^{(l)}\mathcal{I}_{(m-u-1)(n-v-1)}^{(l)}\right\} \quad (3)$$

where $\underline{\underline{\mathcal{K}}}^{(l)} = \left\{\mathcal{K}_{uv}^{(l)};\, u = 1, ..., F;\, v = 1, ..., F\right\}$ denotes the l-th *trainable* convolution filter of dimensions $(F \times F)$. The entries of the convolution filters, $\left\{\mathcal{K}_{uv}^{(l)};\, u = 1, ..., F;\, v = 1, ..., F\right\}$, as well as the weights of the *FCNN*, $\{w_{mn}^{q};\, m = 1, ..., M;\, n = 1, ..., N\}$, are determined during the off-line training phase by minimizing a suitable *loss function* that quantifies the mismatch between the t-th ($t = 1, ..., T$) function/output value, $\underline{\Phi}(\underline{\Omega}_t)$, and the corresponding estimated value, $\underline{\widetilde{\Phi}}(\underline{\Omega}_t)$, computed according to (1) [11]. As for the *pooling* layers, the l-th output, $\underline{\underline{\mathcal{O}}}^{(l)} \triangleq \mathcal{P}^{(l)}\left\{\underline{\underline{\mathcal{I}}}^{(l)}\right\}$, is typically defined as the maximum over a set of neighboring input entries

$$\mathcal{O}_{mn}^{(l)} = \max_{i,\,j=0,\,...,\,P-1}\left\{\mathcal{I}_{[(m-1)\times s+i][(n-1)\times s+j]}^{(l)}\right\} \quad (4)$$

P being the *pooling size* and s the *stride* determining the interval between neighboring pooling windows. It is worth observing that the purpose of *convolution* and *pooling* layers is to extract low-dimension/highly-informative *features* able to accurately model the underlying *I/O* relationship, $\underline{\Phi}$. As a matter of fact, the main advantage of *CNN*s over conventional *NN*s is their capability of "*feature learning*" with translational/rotational invariance directly from training data, provided that the input exhibits some local correlation as in natural images [13]. On the other hand, *RNN*s are suitable to model time series data, in which each sample is assumed to be dependent on the previous one, especially when coupled with memory [13].

III. Applications

EM Scattering: (*a*) Forward Scattering *(FS)* - Finite element method (*FEM*) [14], method of moments (*MoM*) [15], and finite difference time domain (*FDTD*) [16] are popular computational tools for solving forward *EM* problems formulated in terms of differential and/or integral equations to be discretized in matrix systems, which are generally characterized by millions of unknowns when dealing with real scenarios/applications. This implies non-negligible computational issues because of the high complexity of the numerical problems at hand [14]. Therefore, solving forward *EM* problems in real-time is still very challenging and *DNN*s are rapidly emerging as a promising candidate to dramatically speed up standard *EM FS* solvers [1][17]-[21]. Two novel strategies based on deep *RNN*s and *CNN*s have been recently proposed to efficiently solve *FDTD* problems [17]. Moreover, a real-time *EM* Poisson's equations solver based on *DL* has been introduced in [18] to predict the distribution of the potential of the electrostatic field in 3*D* domains. Towards this end, a *CNN* has been trained to learn the *NL* relation between the source-location/permittivity-distribution and the potential. Numerical experiments have shown prediction errors smaller than 3% despite the significant reduction of the computation time with respect to a standard full-wave (*FW*) approach [18]. Similarly, faithful computations of the *EM* field scattered by 2*D* inhomogeneous circular objects have been obtained by training a *CNN* with finite-element boundary integral (*FEBI*) *FW* simulations [19]. Deep *FFNN*s have been also successfully exploited in estimating the *EM* interferences radiated by extra-high speed electronic devices and systems to enable the computationally-efficient design of printed circuit boards with reduced emissions [20]. Furthermore, a *FFNN* architecture has been adopted in [21] for determining the magnetic flux in unbalanced induction motors. Finally, a *DL* approach has proven to give almost real-time performance, $\Delta t \approx 1$ [sec], in computing the waveforms generated by a ground penetrating radar (*GPR*) in a 3*D* subsurface scenario [1]. It is worth pointing out that *DNN*s for *FS* are in the very early stages of development, clearly representing a promising solution to accelerate computations of traditional solvers. However, significant efforts are still needed to investigate the correlation between *DNN*s operations and *EM* algorithms in order to develop much faster and yet accurate forward solvers.

(*b*) Inverse Scattering *(IS)* - Inverse scattering problems (*ISP*s) are aimed at retrieving *qualitative* (i.e., location and shape) and *quantitative* (i.e., material composition) information on unknown targets from non-invasive measurements of the scattered field [22]. The first attempts to solve *ISP*s with *shallow NN*s have been concerned with the *parametric* inversion of the scatterers (i.e., positions, geometries, and homogeneous dielectric properties) [23][24]. Although the application of *DNN*s to *ISP*s is at an early stage, they are rapidly gaining attention thanks to their efficiency to manage a more versatile *pixel-based* representation of the unknown distributions of the *ISP* [2][25]-[32]. In this framework, three *CNN*-based approaches have been proposed in [2]. While the direct inversion scheme (*DIS*), devoted to estimate the permittivity profile starting from scattered field measurements, yielded non-optimal results, the other two approaches, both based on the *CNN*-processing of low-quality/low-pass guesses generated by non-iterative algorithms, successfully performed thanks to the effectiveness of *CNN*s in restoring missing details and removing artifacts in degraded images. More specifically, the dominant current scheme (*DCS*) approach [22] turned out to be more competitive than relying on the back-propagation (*BP*), carefully retrieving complex-shape targets in just $\Delta t \leq 1$ [sec] [2]. It is worth noticing that *BP* has been also adopted in [25] to give *pre-processed* inputs/reconstructions to the *CNN*. On the other hand, the connection between conventional iterative *IS* algorithms and *DNN*s has been profitably investigated in [26] to develop the "*deepNIS"* inversion method, which is based on three-cascaded *CNN*s that process a *complex-valued* input (i.e., a *BP*-generated image) to determine a super-resolution guess of the dielectric distribution of the investigation domain [26]. Alternatively, a significant reduction of the *CPU*-time required by gradient-like deterministic retrieval techniques has been yielded by training a *DNN* to learn descent directions [27][28]. On the other hand, two reconstruction algorithms based on an *AE* and a *FCNN*, respectively, [29] outperformed traditional algorithms in terms of both accuracy and processing time (e.g., $\Delta t = 0.03$ [sec] for the *FCNN* solution [29]). Moving to biomedical imaging applications of the *IS*, *DNN*s are common tools within the image processing community to perform classification and segmentation as, for example, for the detection of melanoma and lymph node [30]. More recently, the "*Deep D-Bar*" approach [31] and a *DCS*-based technique [32] have been proposed for the real-time (e.g., $\Delta t < 8$ [ms]) electrical impedance tomography (*EIT*) of the chest. According to authors' vision, *DL* could provide a way to incorporate more versatile *prior* information to mitigate the *ill-posedness* which would be hard to express in a rigorous mathematical formulation [27].

DIRECTION-OF-ARRIVAL (*DoA*) ESTIMATION - *DoA* estimation is an attractive field of research with many applications including communications, radar, and astronomy. Many efforts have been recently devoted to develop innovative methods with high angular resolution and robustness to the noise able to deal with limited data from few/single snapshots [33], as well. In such a framework, *DNN*s are key-solutions because of their intrinsic efficiency in learning very complex propagation models from the available training data [3][34]-[36]. For instance, a new *DL* framework for *DoA* estimation has been presented in [3]. More in detail, a multitask *AE* has been used to filter and to decompose the input signal into spatial sub-regions successively processed by a series of classifiers to detect the presence of signals along with (or close to) predefined grid directions. Numerical results have assessed the enhancement of the *DoA* performance as well as the improvement of the generalization capabilities in comparison with the commonly adopted MUltiple SIgnal Classification (*MUSIC*) [3]. In [35], super-resolution *DoA* estimation and signal detection have been addressed with *DNN*s by leveraging on the powerful recognition and representation abilities of *DL*s in the presence of real-time and continuous changes of the *EM* channel conditions. Dealing with very high-frequency (*VHF*) radars under strong multi-path and complex terrains [36], an *AE*-based method has proved to work better than *MUSIC* in handling spatially-adjacent coherent sources.

RADAR AND REMOTE SENSING (*RS*) - Scattering and speckle are big issues in air-/space-borne synthetic aperture radar (*SAR*) imagery and the development of robust and reliable techniques is mandatory for the interpretation and understanding of the produced images. *DNNs* are natural candidates for performing accurate automatic target recognitions (*ATR*s) [4][37][38]. In [4], a *CNN* has been implemented for high-accuracy image classification to avoid overfitting when small training databases are at hand. Similarly, a *generative DNN* has been trained in [37] to learn a hierarchical representation of the features of *SAR* targets. On the other hand, polarimetric *SAR* (*PolSAR*) image classification has been addressed with a deep *CNN* incorporating expert knowledge on the interpretation the scattering mechanisms and polarimetric feature mining [38]. Moreover, a novel *CNN* inversion method for rough surface estimation has been discussed in [39] by proposing the generation of synthetic training samples as solutions of an *ISP*, then letting the *CNN* learn the *NL* relationship between inverted images and predicted surface descriptors. Moreover, *DNN*s have been used for microwave *RS* of vegetated terrains in [40] where a *ML* scheme has been invoked to faithfully predict the polarimetric bistatic scattering cross section of a finite dielectric cylinder modelling a corn canopy in *C*-Band. Starting from the idea that every medium has a unique radar *signature* when illuminated by an *EM* probing wave, the "*radar-Siamese*" *NN* (*R-SiameseNet*) has been developed to automatically extract robust features for an accurate material classification [41]. *DL* is also rapidly emerging in *GPR* signal processing and imaging [1][42] for buried object classification [43], material identification [44], and landmine detection [45].

COGNITIVE RADIO (*CR*) AND *MIMO* SYSTEMS - The *smart* and efficient use and allocation of (limited) radio resources is nowadays a pillar feature in view of the ever-growing proliferation of wireless systems and services and the imminent deployment of fifth-generation (5*G*) communications [46][47]. Indeed, there is an urgent need of systems able to sense the surrounding *EM* environment and reconfigure the radiating system (Tx/Rx) for guaranteeing reliable and high-rate communications. Dealing with *MIMO* systems for increasing the spectral/spatial efficiency as well as the system throughput, as required in cognitive radio (*CR*) systems [46][47], *DNN*s have been widely involved to reach a good coverage and the capacity optimization in massive *MIMO* (*M-MIMO*) [5]. To perform channel estimation in millimeter-wave (*mmWave*) *MIMO*, a *DNN*-based approach has been presented in [48] by interpreting the channel matrix as a 2*D* image on which a denoising *CNN* (*DnCNN*) has been applied to achieve remarkable performance with a limited number of *RF* chains at the receiver, as well. On the other hand, *DL* has been recently proposed to mitigate the inter-cell interferences in 5*G M-MIMO* systems [49] for an efficient pilot signal allocation with performance close to the theoretical upper-bound ($\approx 99.38\%$) in only $\Delta t = 0.92$ [ms]. Finally, fast beamforming techniques based on *DNN*s have been recently applied to down-link transmissions in *MIMO* [50] and *mmWave* communications [51] for both in line-of-sight (*LOS*) and non-*LOS* scenarios.

OTHER EM-RELATED APPLICATIONS - *DNN*s have been also recently applied to other *EM*-related research fields. For instance, it is worth mentioning indoor [6][52][53] and outdoor [54] localization. In [52], channel state information *CSI* phase measurements have been processed to estimate the location of a mobile device, while the angle of arrival (*AoA*) and the average *CSI* amplitudes have been used for indoor localization just using available 5 GHz *WiFi* networks (i.e., without extra/ad-hoc infrastructures) with deep *AE*s [6] and *CNN*s [53]. Moreover, an innovative *AE*-based "channel charting" strategy has been proposed to learn the mapping between the *CSI* signals, acquired at a single base-station, and the relative user/transmitter locations. Another topical application of *DL* concerns human behavior monitoring for remote health supervision, athletic training, and contactless control of devices [7][55][56][57]. As for hand gesture recognition, robust outcomes have been yielded by *CNN*s processing micro-Doppler signatures/spectrograms [56] or the input impedance variations in monopole antennas [57]. On the other hand, the spectrograms derived from the *EM* interactions around the human neck due to the *creeping* waves produced by two on-body antennas working at 2.45 [GHz] have been used to train a *CNN* for monitoring and classifying different head- and mouth-related motions [55]. Similarly, the classification of human activities from the measurements of the transmission and the reflection coefficient at the terminals of on-body antennas has been performed with a *CNN*-classifier giving an accuracy higher than 97% [7]. Finally, pioneering works have explored the applicability of *DNN*s to the automatic identification of *RF* rogue and/or unknown transmitters from received waveforms [58], to the high-speed channel modeling [59], and to *EMC* analyses [8].

IV. FINAL REMARKS AND FUTURE TRENDS

An overview of the most recent advances in *DNN*s as applied to *EM* has been presented by reviewing the literature on the topic. Addressed applications mainly represent the first attempts to extend/improve the capabilities of canonical *ML* techniques already exploited in such contexts [9]. According to the authors' vision, *DL* will soon become a dominant paradigm in solving high-complexity real problems at the basis of several key *EM* applications/scenarios. Of course significant efforts are still necessary to address paramount unsolved challenges such as (*i*) the reduction of the computational burden and of the amount of training data for the *off-line* phase, (*ii*) the study of *reinforcement learning* strategies that dynamically self-adapt to the continuously-changing working conditions [11], and (*iii*) the exploitation of the available information on the underlying *EM* physics and of non-*ML* strategies to improve the *DNN* performance by optimally choosing inputs/outputs as well as the loss training function. The use of *unsupervised* methods [11] to better mimic the human/animal learning should be further investigated. As for the local minima occurring in the loss function, evolutionary optimization [60] could represent an effective solution for a more robust tuning of *DNN*s parameters. However, recent works have shown that for large networks the majority of local minima are almost equivalent in terms of cost function, suggesting that selecting one sub-optimal solution could be sufficient in many practical contexts [13]. One main disadvantage of *DNN*s is the very high number of parameters and hyper-parameters to set. However, much more complex *EM* problems could in principle be modeled thanks to the larger number of degrees of freedom with respect to conventional *NN*s [9][13]. On the other hand, to the authors' best knowledge, differently from classification *DNN*s for regression still don't have obvious advantages over traditional solvers in terms of achievable accuracy [61]. As for innovative applications, *DL* will clearly be a key-asset in addressing the analysis/synthesis of complex antenna systems comprising a large number of degrees-of-freedom (e.g., reflectarrays [62][63]). More in general, *DNN*s will be an interesting solution in applicative fields requiring *self-learning* form experiences, including wireless sensor networks (*WSN*s) and decision support systems (*DSS*s) [64]. As for the adaptability of general *DNNs/CNNs/RNNs* on *EM* applications, innovative complex-valued architectures should be studied to properly deal with complex quantities (e.g., field patterns, scattering/transmission coefficients, etc. [65]). On the other hand, understanding the correlation between *DNN*s computations and forward/inverse solvers, as well as properly modifying them to better fit the addressed problems, will enable a more effective exploitation of *DL* in *EM* without just regarding it as a powerful but unknown "black-box". Many questions are still open and are here reported for a readers' further thinking and reading: which part of the problem can be solved through *DNN*s in a better way? What aspects of *DNN* are better? Are *DNN*-based approaches more robust? Are accuracy/efficiency metrics enough to evaluate and justify such methods? What are the relationship and possible gap with traditional methods?.

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